Flight Control Systems That Learn

Silvia Ferrari

Advisor: Prof. Robert F. Stengel

Princeton University

FAA/NASA Joint University Program on Air Transportation,

NASA Ames Research Center, Moffett Field, CA

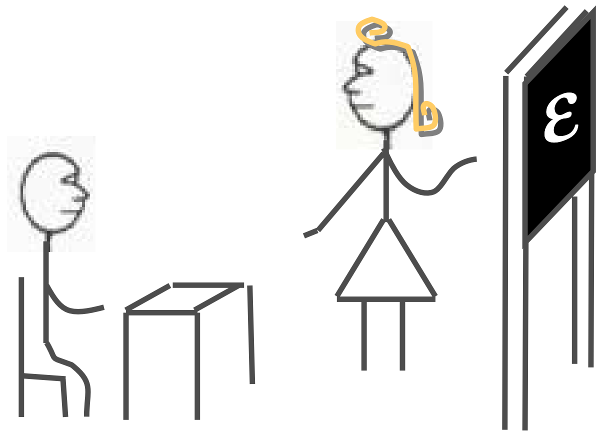
April 4-5, 2002

A Multiphase Learning Approach for Automated Reasoning

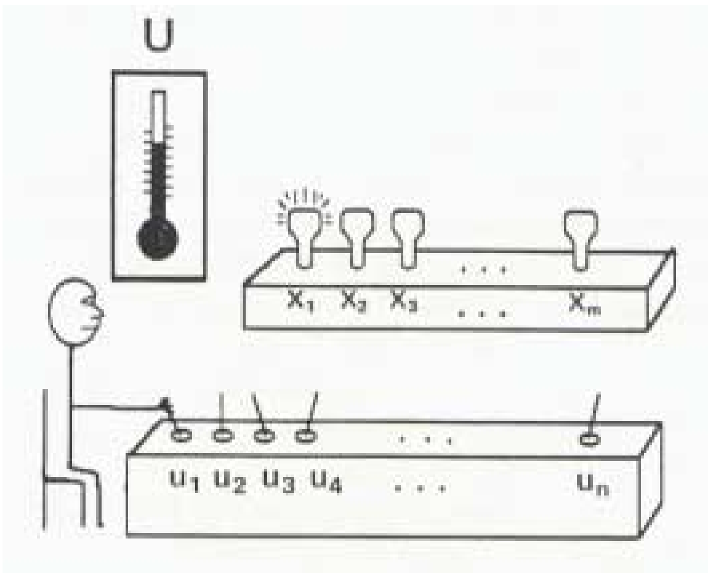
On-line

Control	Routing
Identification	Scheduling
Planning	...

Supervised Learning:



Reinforcement Learning:



The same performance metric is optimized during both phases!

Introduction

- Stringent operational requirements introduce
  Complexity
  Nonlinearity
  Uncertainty

- Classical/neural synthesis of control systems
  A-priori knowledge
  Adaptive neural networks

- Dual heuristic programming adaptive critic architecture:

  Action network takes immediate control action

  Critic network estimates projected cost

Neural Network Control of Aircraft

- Full envelope control

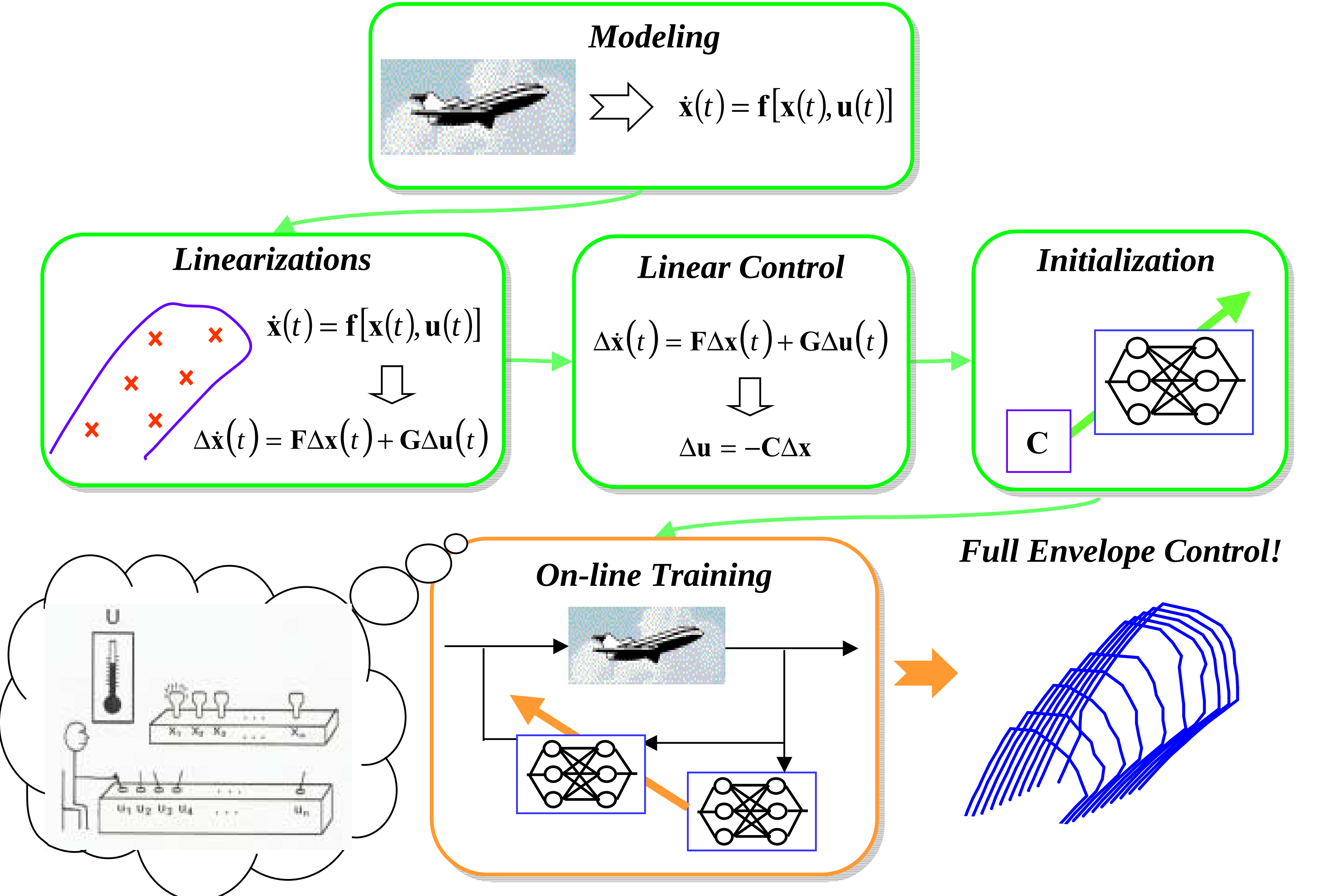
- Multiphase learning
  Initialization: match linear controllers exactly off-line
  On-line learning: full-scale simulations, testing, or operation

- On-line learning improves performance w.r.t. linear controllers:
  Differences between actual and assumed models
  Nonlinear effects not captured in linearizations

- Potential applications:
  Incorporate pilot's knowledge into controller *a priori*
  Uninhabited air vehicles control
  Aerobatic flight control

Table of Contents

Design Approach



Linear Control Design

Linearizations:

$$\dot{\mathbf{x}}(t) = \mathbf{f}[\mathbf{x}(t), \mathbf{u}(t), \mathbf{p}(t)]$$

$$\Downarrow$$

$$\Delta\dot{\mathbf{x}}(t) = \mathbf{F}\Delta\mathbf{x}(t) + \mathbf{G}\Delta\mathbf{u}(t)$$

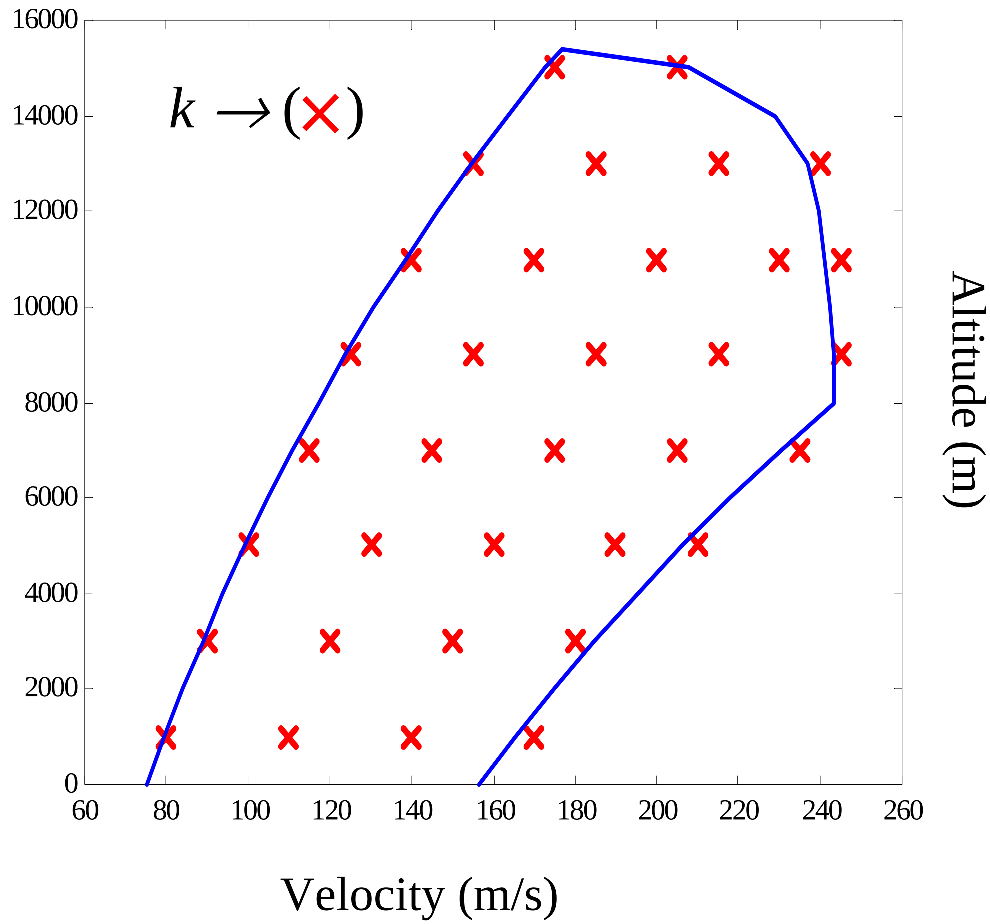
$$\Downarrow$$

$$\begin{cases} \Delta\dot{\mathbf{x}}_L(t) = \mathbf{F}_L\Delta\mathbf{x}_L(t) + \mathbf{G}_L\Delta\mathbf{u}_L(t) \\ \Delta\dot{\mathbf{x}}_{LD}(t) = \mathbf{F}_{LD}\Delta\mathbf{x}_{LD}(t) + \mathbf{G}_{LD}\Delta\mathbf{u}_{LD}(t) \end{cases}$$

Linear control design:

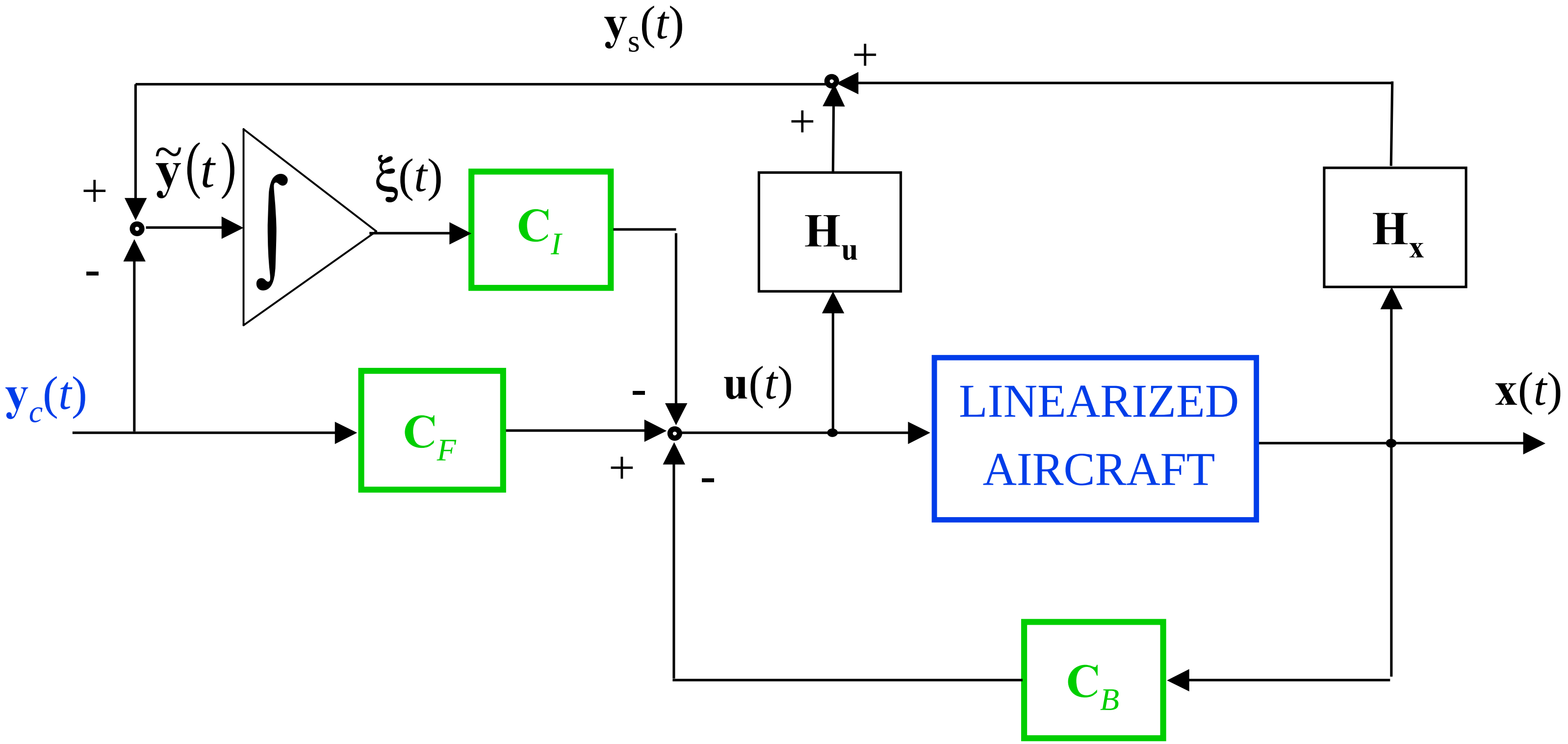
- Longitudinal
- Lateral-directional

Flight envelope and design points:
$(\gamma = \mu = \beta = 0)$



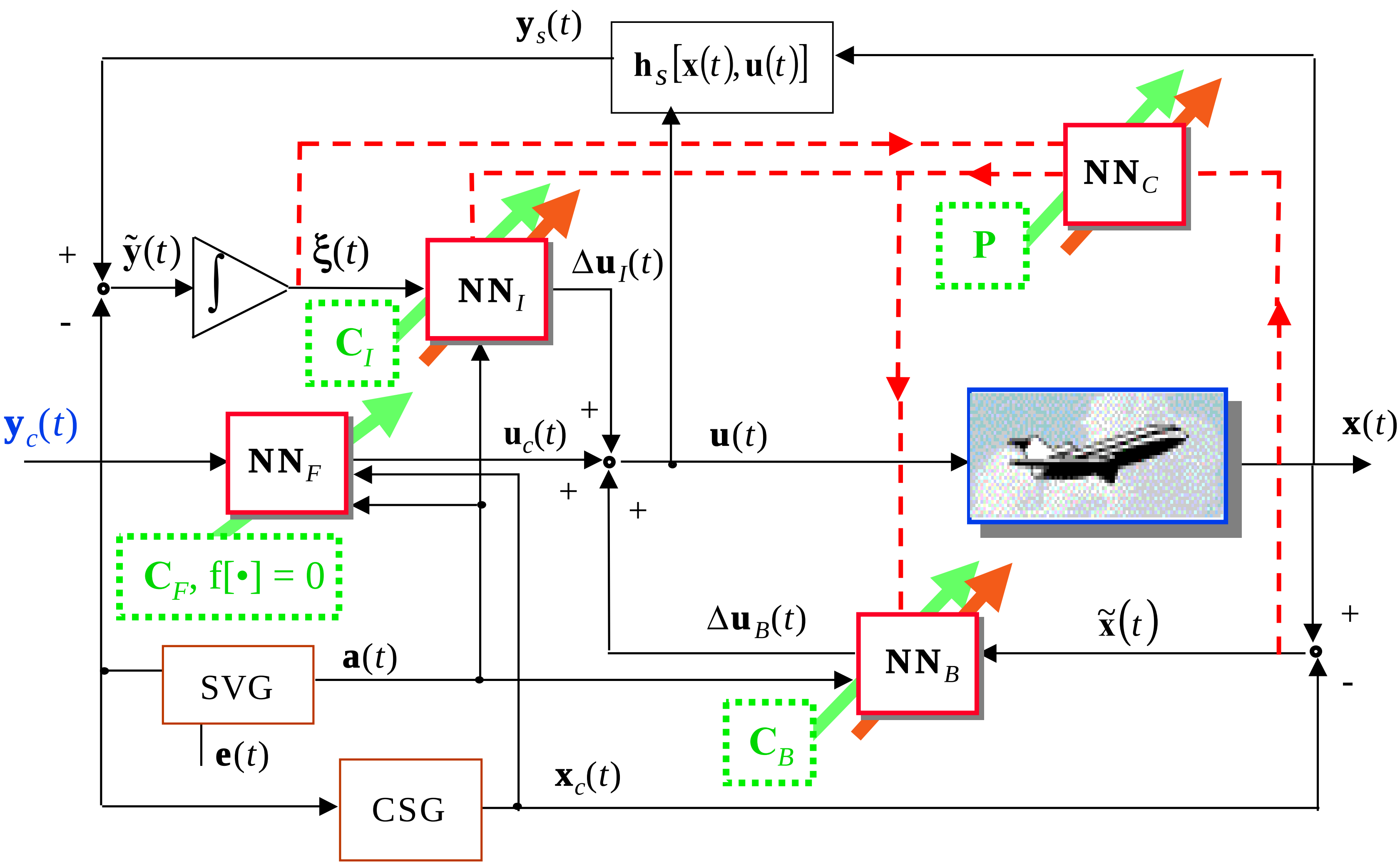
Proportional-Integral Linear Controller

Closed-loop stability: $\mathbf{x} \equiv \mathbf{x} - \mathbf{x}_C \rightarrow \mathbf{0}; \quad \tilde{\mathbf{u}},\ \tilde{\mathbf{y}} \rightarrow 0$



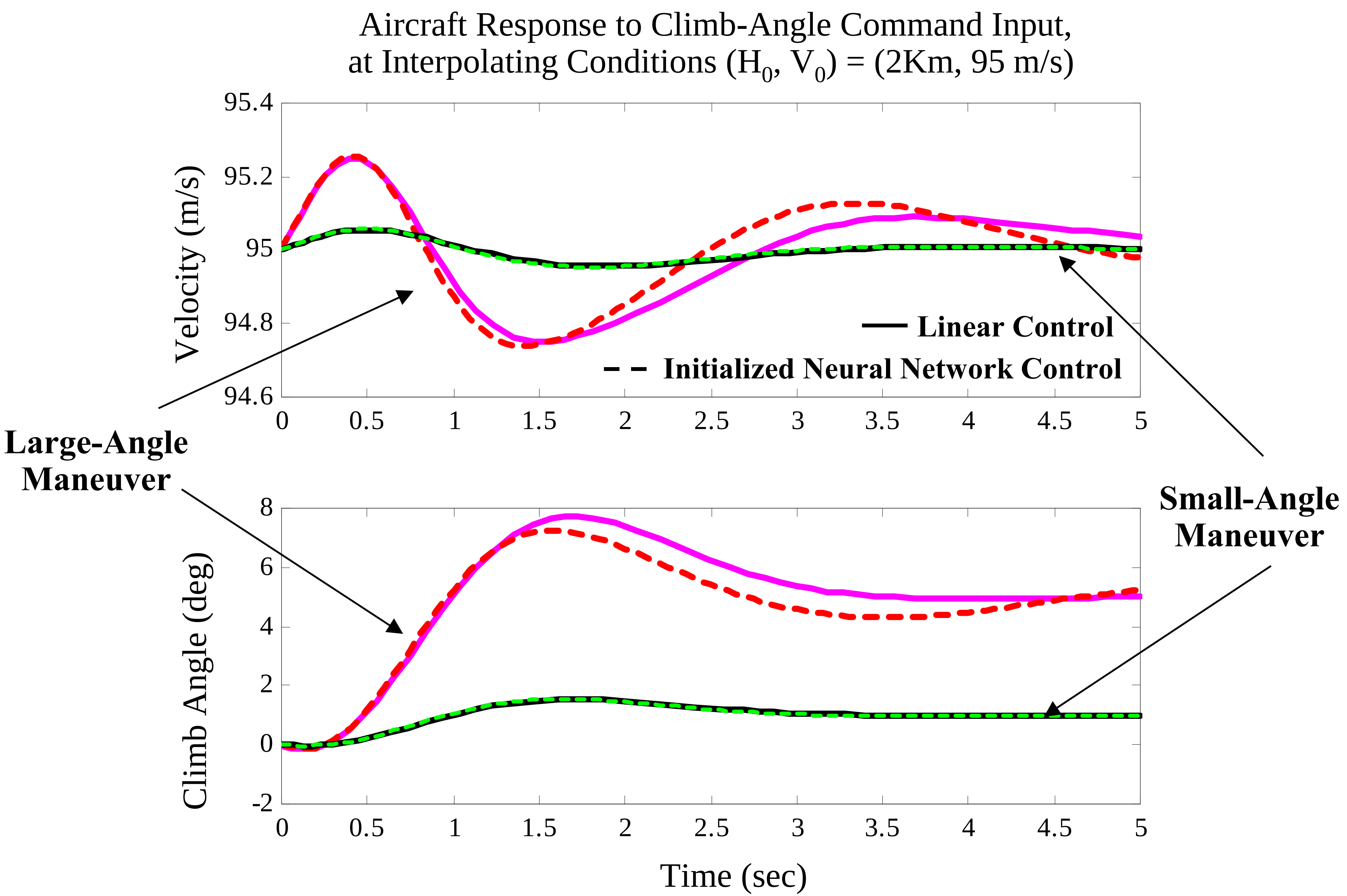
$$J = \lim_{t_f \to \infty} \frac{1}{2} \int_0^{t_f} \left[\mathbf{x}_a^T(\tau)\mathbf{Q}\mathbf{x}_a(\tau) + 2\mathbf{x}_a^T(\tau)\mathbf{M}\tilde{\mathbf{u}}(\tau) + \tilde{\mathbf{u}}^T(\tau)\mathbf{R}\tilde{\mathbf{u}}(\tau) \right] d\tau, \quad \mathbf{x}_a \equiv \left[\tilde{\mathbf{x}}^T \quad \xi^T \right]^T$$

Proportional-Integral Neural Network Controller

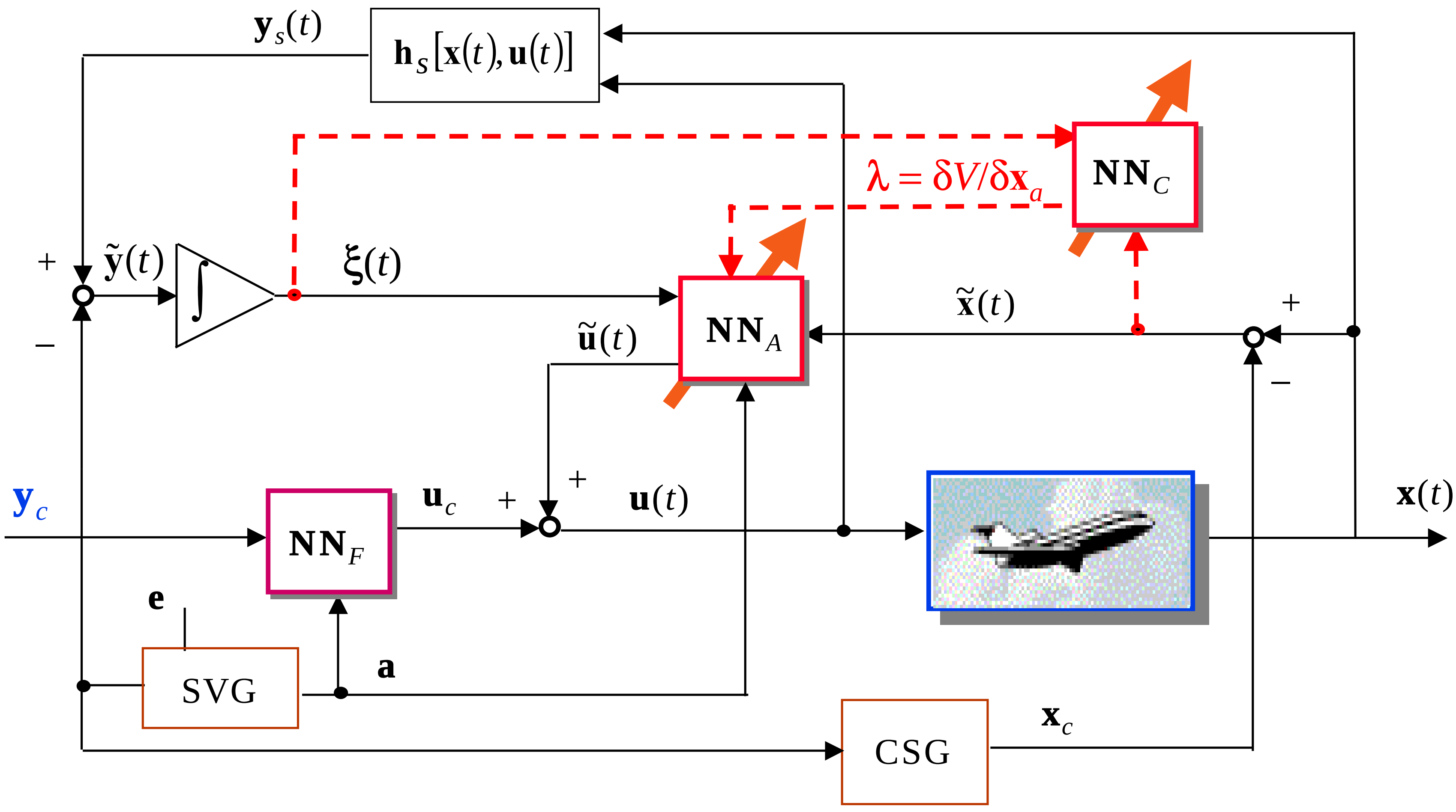


: Algebraic Initialization, : On-line Training.

Comparison of Initialized Neural Network and Linear Controllers



Proportional-Integral Neural Network Controller On-line Adaptation



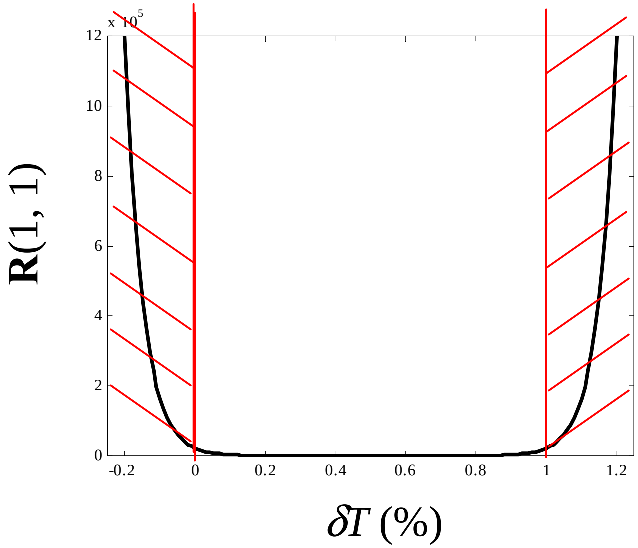
$$V(t) = -\lim_{t_f \to \infty} \frac{1}{2t_f} \int^{t} \left[\mathbf{x}_a^T(\tau)\mathbf{Q}\mathbf{x}_a(\tau) + 2\mathbf{x}_a^\tau(\tau)\mathbf{M}\tilde{\mathbf{u}}(\tau) + \tilde{\mathbf{u}}^T(\tau)\mathbf{R}\tilde{\mathbf{u}}(\tau)\right] d\tau,$$

On-line Adaptation with Bounded Control Inputs

Introduce exponential cost in the control-weighting matrix **R**:

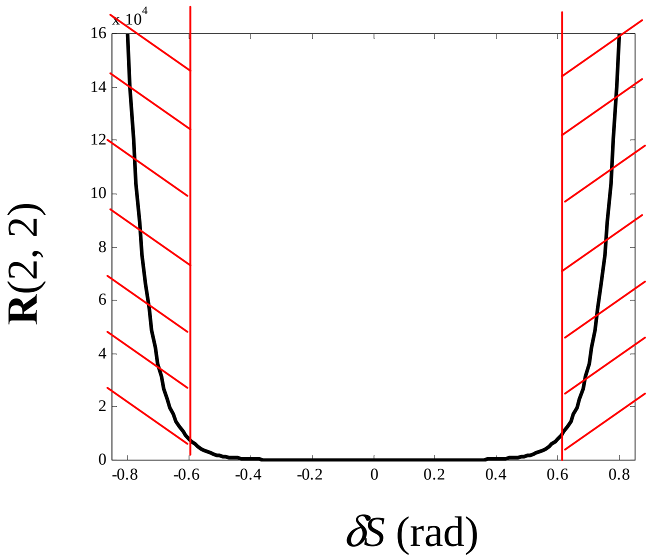
- For bounded throttle, $0 \le \delta T(\%) \le 1$,

$$\mathbf{R}(1,\ 1) = e^{10\left|2\delta T - 1\right|}$$



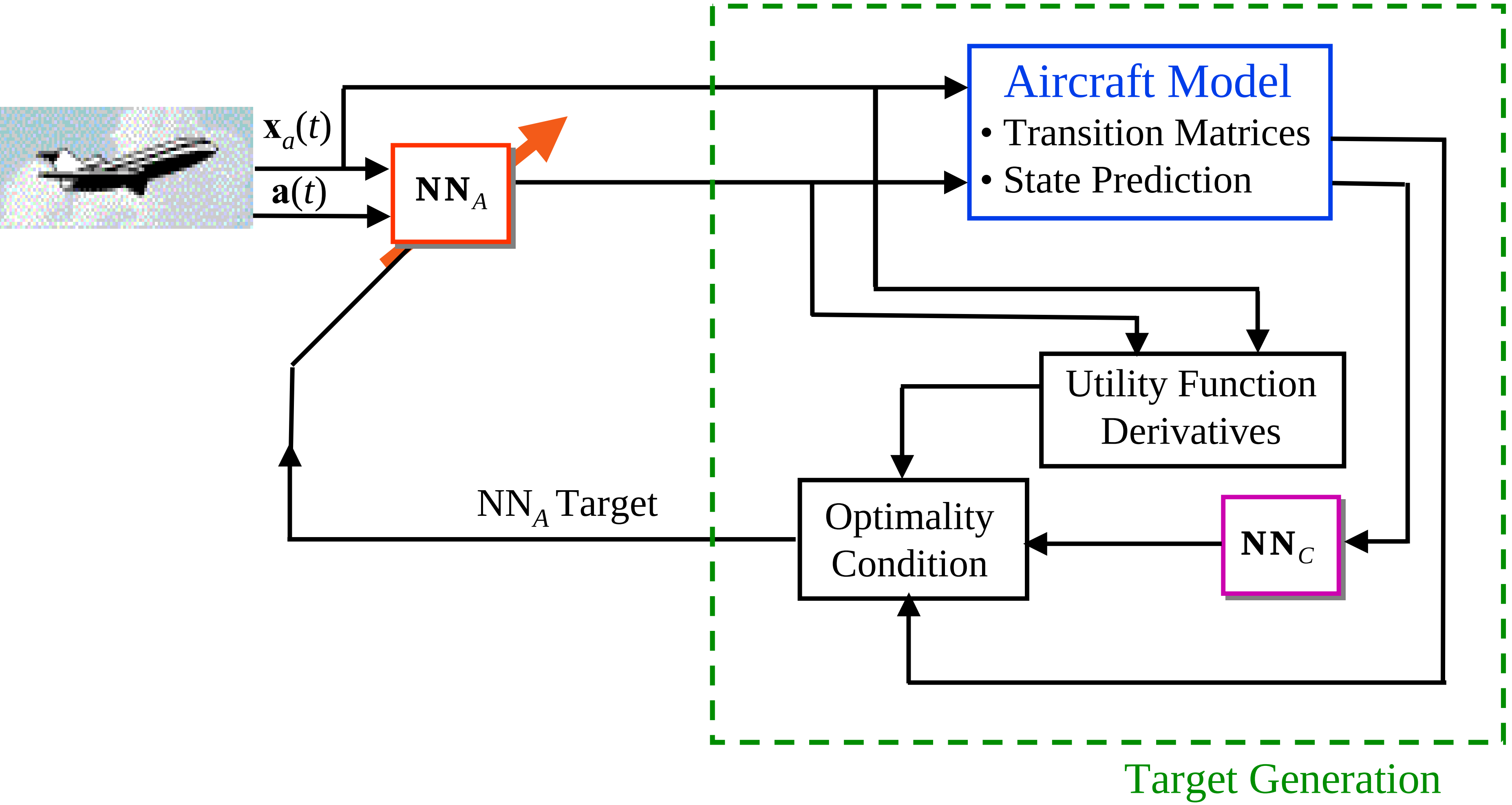
- For bounded stabilator, aileron, and rudder deflections, e.g., $-0.6 \le \delta S(\text{rad}) \le 0.6$,

$$\mathbf{R}(2,\ 2) = e^{15\left|\delta S\right|}$$



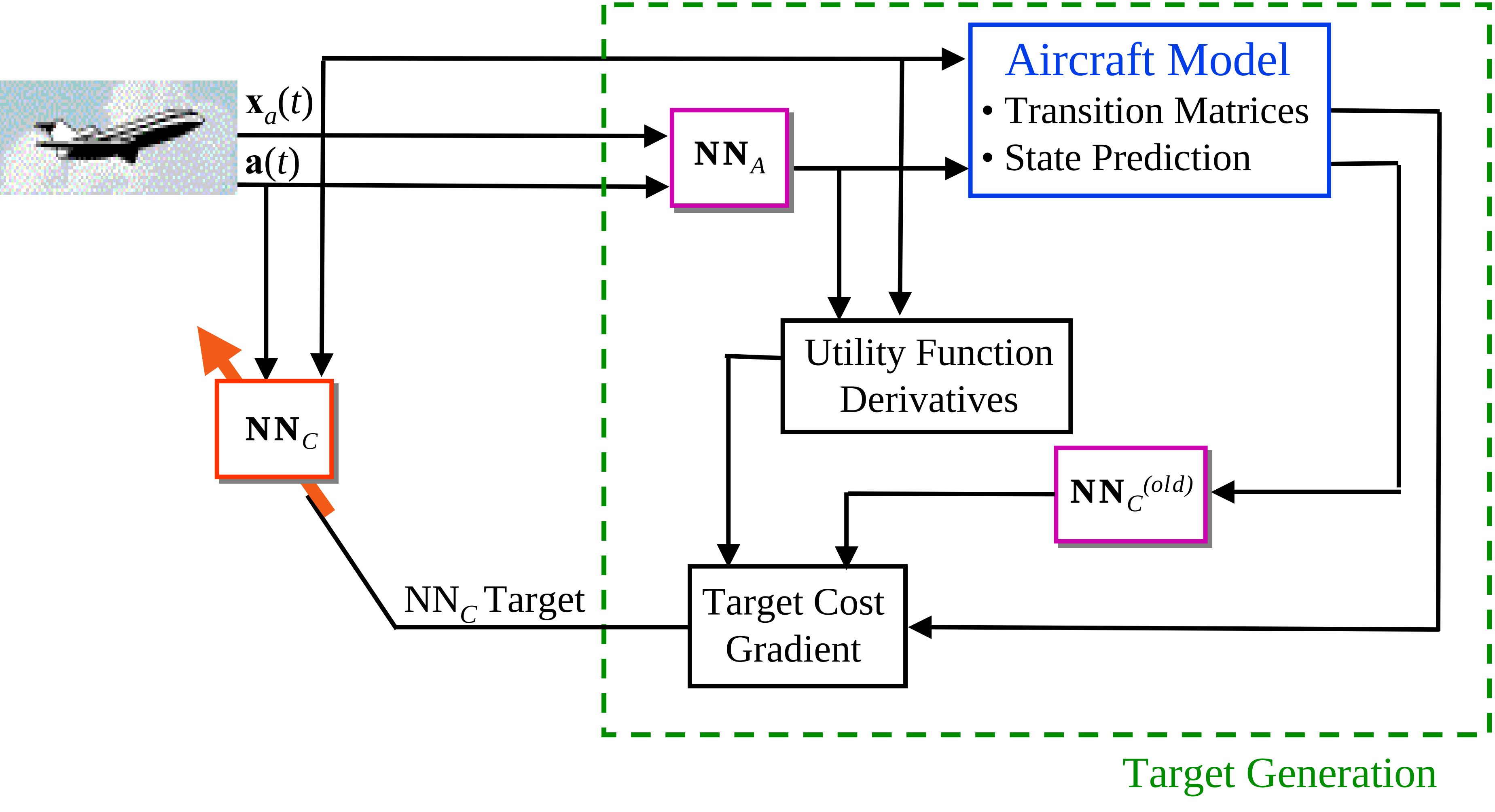
Adaptive Critic Implementation:
Action Network On-line Training

Train action network, at time *t*, holding the critic parameters fixed



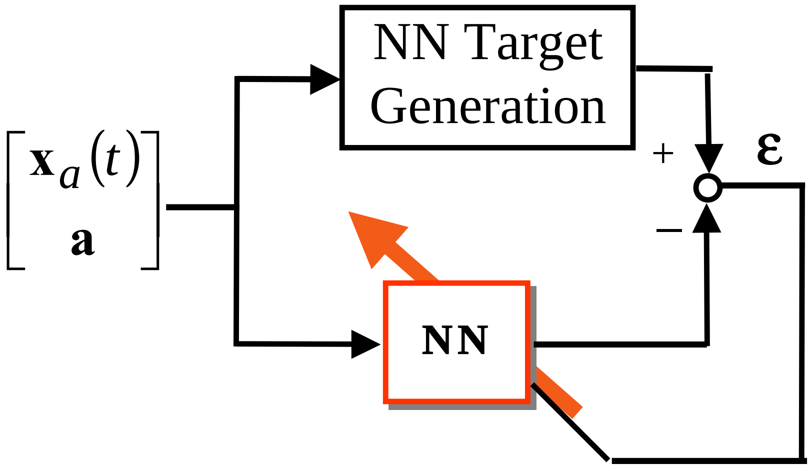
Adaptive Critic Implementation:
Critic Network On-line Training

Train critic network, at time t, holding the action parameters fixed



Action/Critic Network On-line Learning, at Time *t*

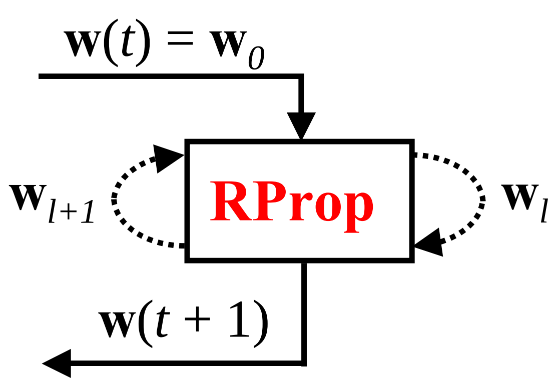
The (action/critic) network must meet its target,



$$\min_{\mathbf{w}} E \equiv \min_{\mathbf{w}} |\boldsymbol{\varepsilon}|^2$$

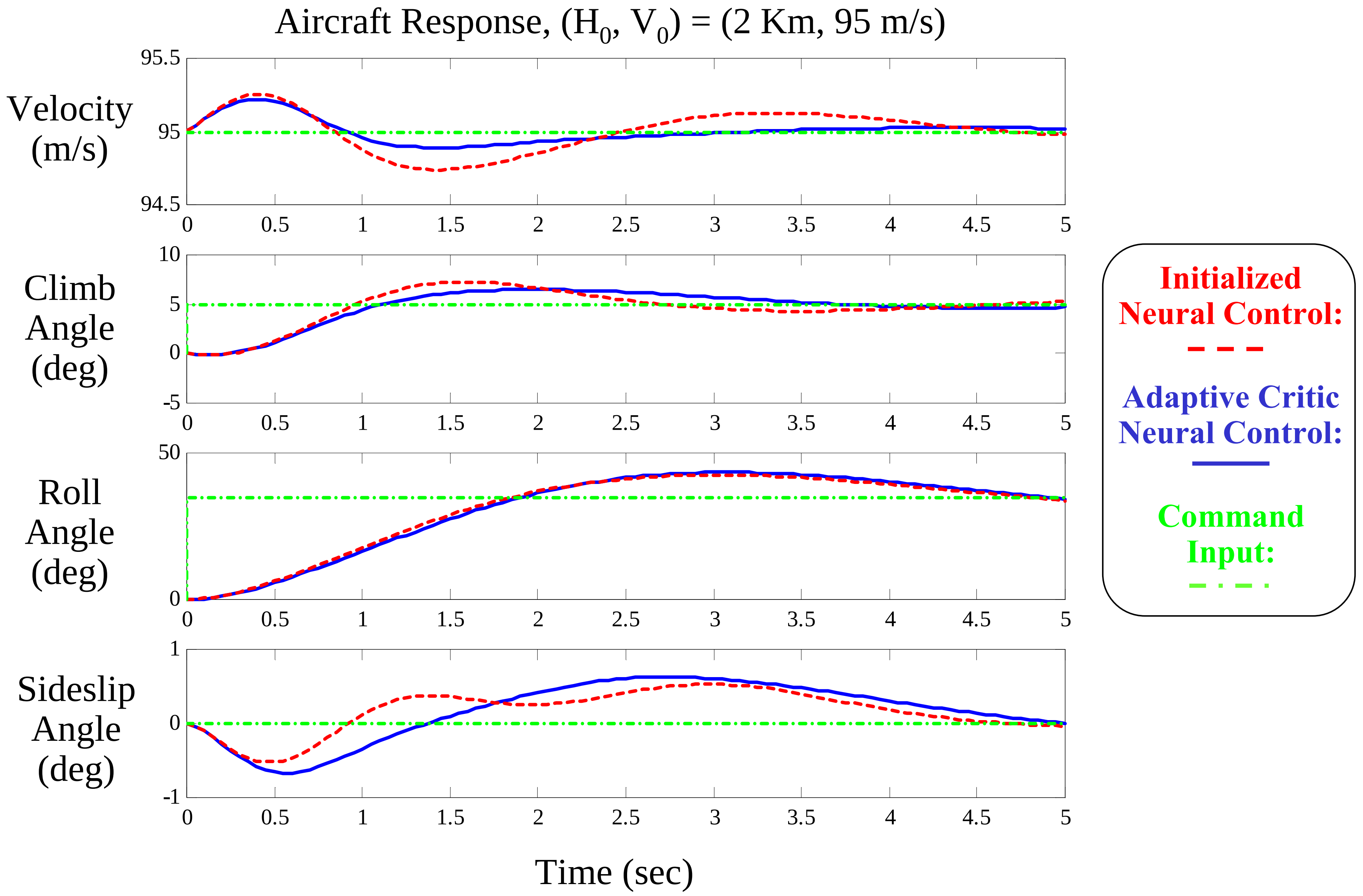
$$\left\{ \begin{array}{l} E \equiv \text{Network performance} \\ \boldsymbol{\varepsilon} \equiv \text{Network error} \\ \mathrm{w} \equiv \text{Network weights} \end{array} \right.$$

Modified Resilient Backpropagation (**RProp**) minimizes E w.r.t. $\mathbf{w}$:

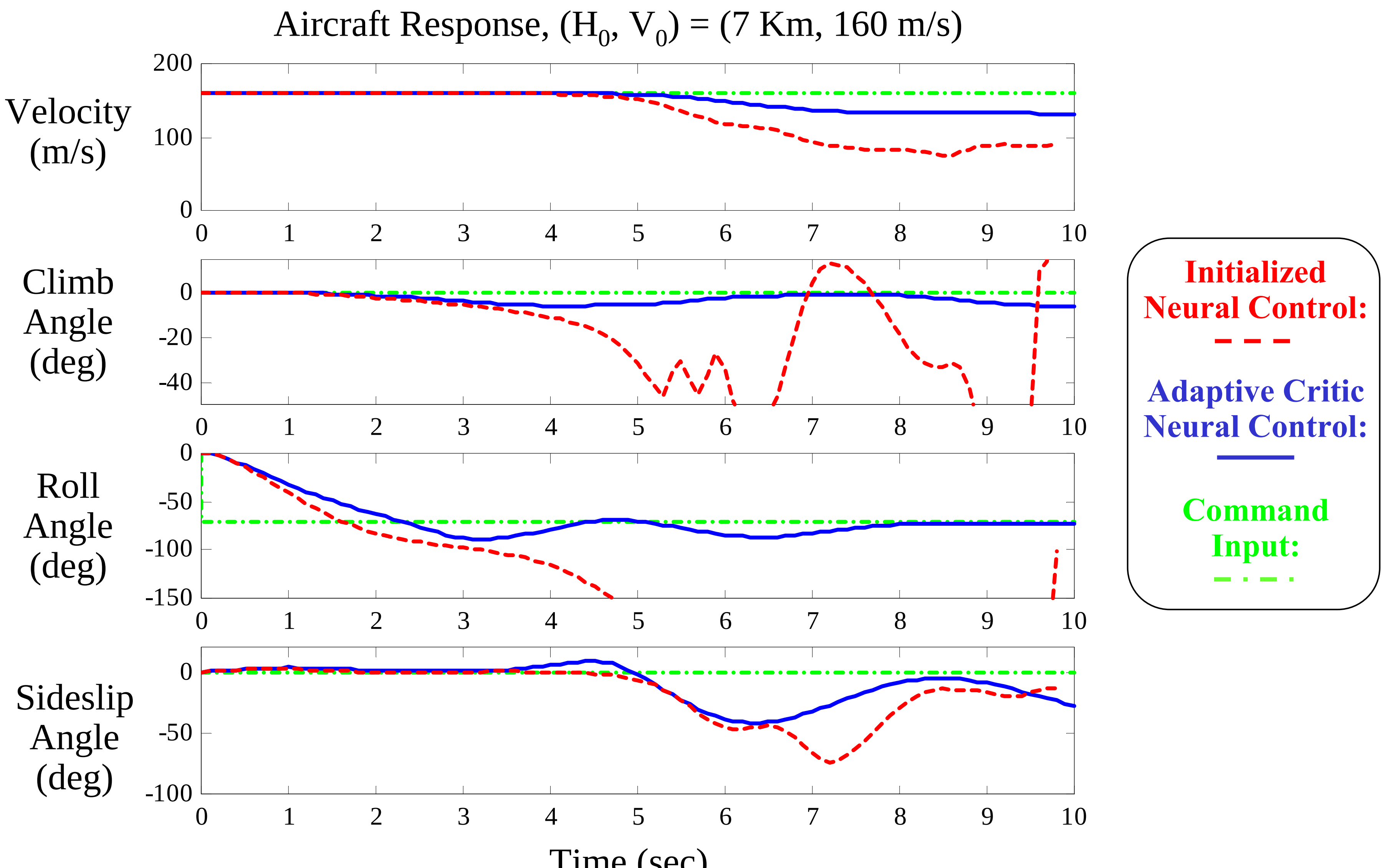


$$\mathbf{w}_{l+1} = \mathbf{w}_l + \Delta\mathbf{w}_l$$

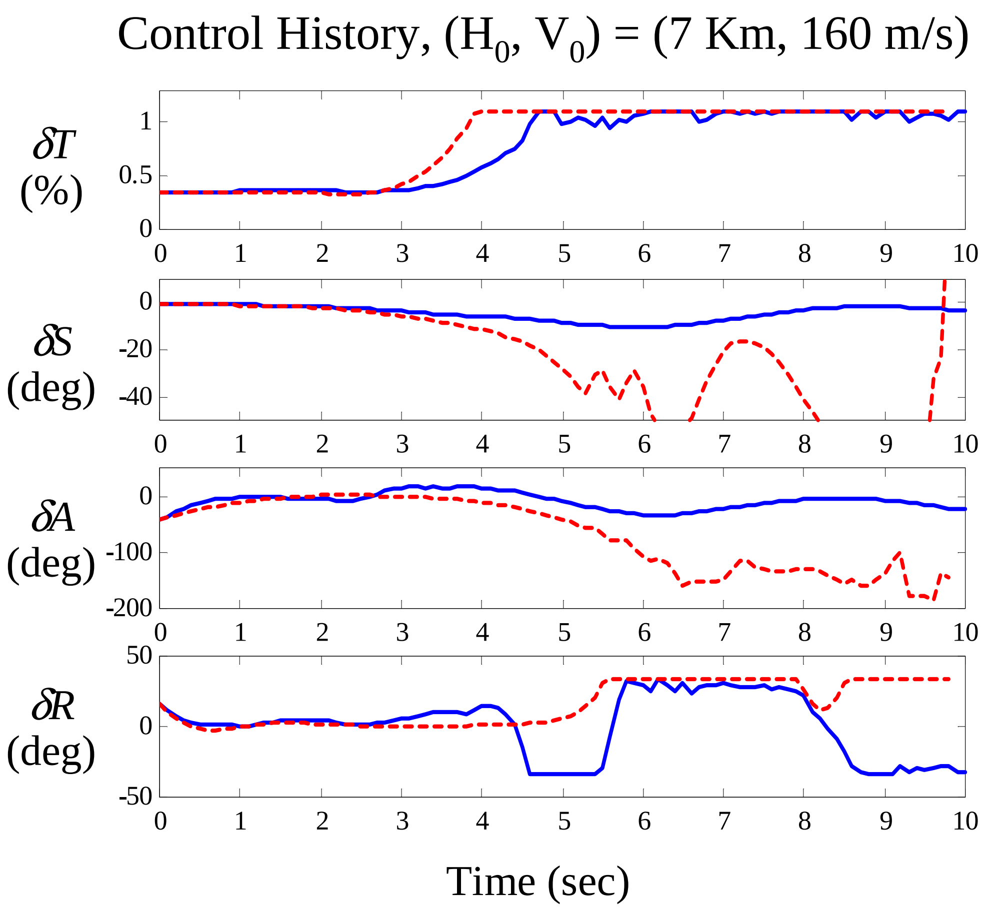
Comparison of Adaptive Critic and Initialized Neural Control: Aircraft Response During a Coupled Maneuver

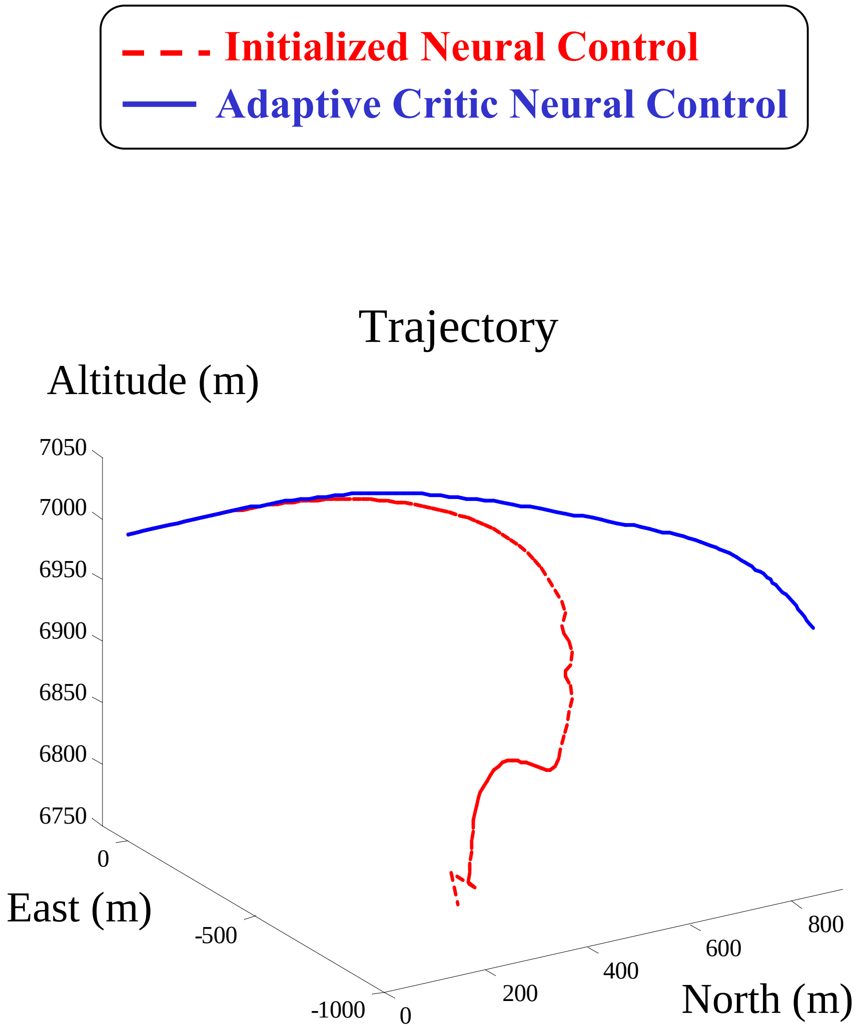


Comparison of Adaptive Critic and Initialized Neural Control: Aircraft Response During a Large-Angle Maneuver



Comparison of Adaptive Critic and Initialized Neural Control During a Large-Angle Maneuver



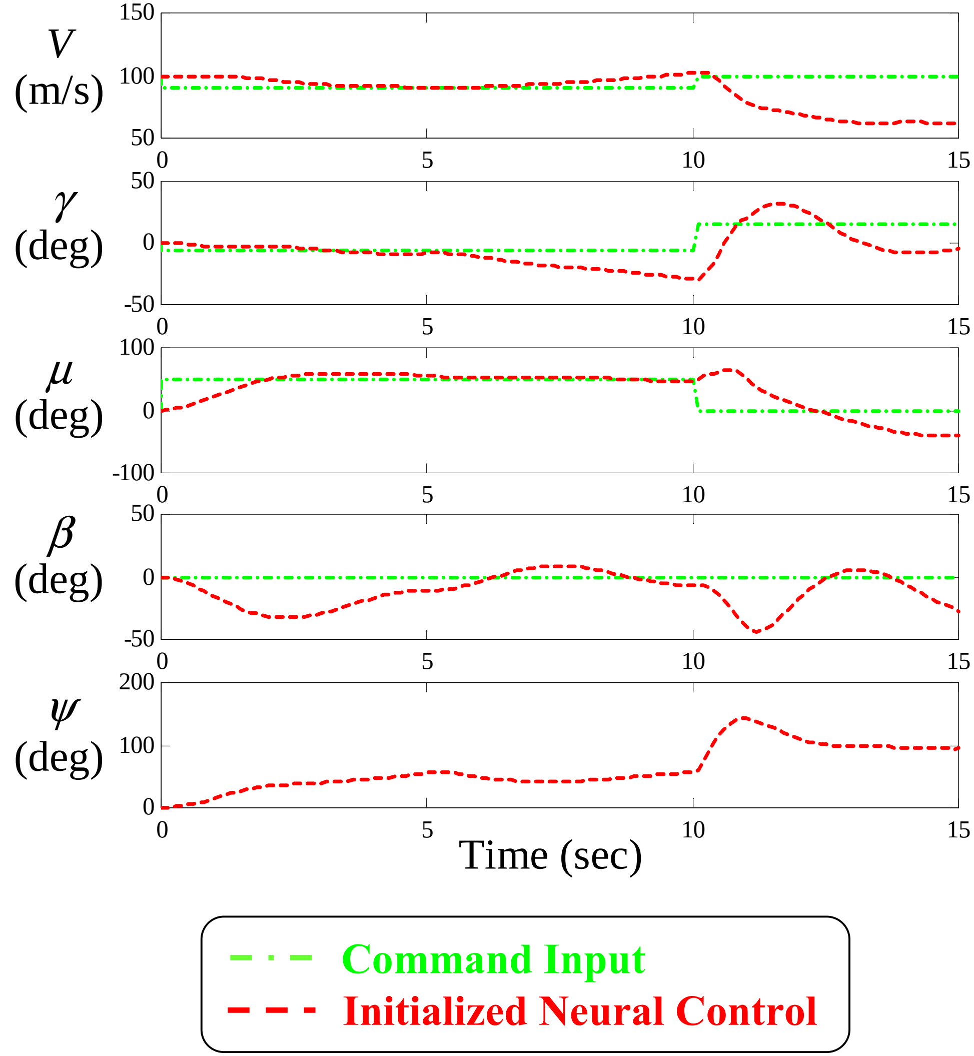


Initialized Neural Controller Performance in the Presence of Control Failures

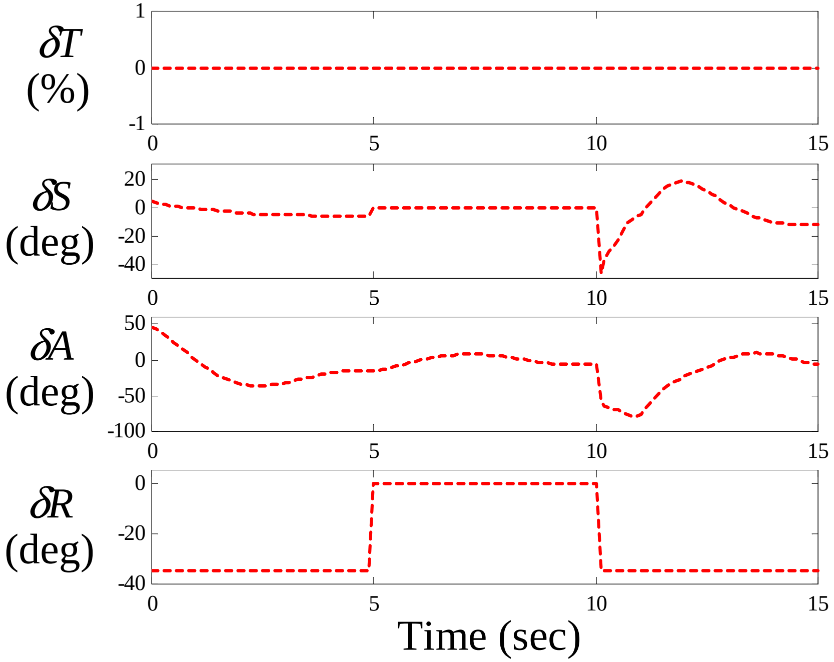
Control Failures:

- $\delta T = 0,\ 0 \le t \le 15$ sec
- $\delta S = 0,\ 5 \le t \le 10$ sec
- $\delta R = 0,\ 5 \le t \le 10$ sec
- $\delta R = -34^{o},\ t \le 5$ or $t \ge 10$ sec

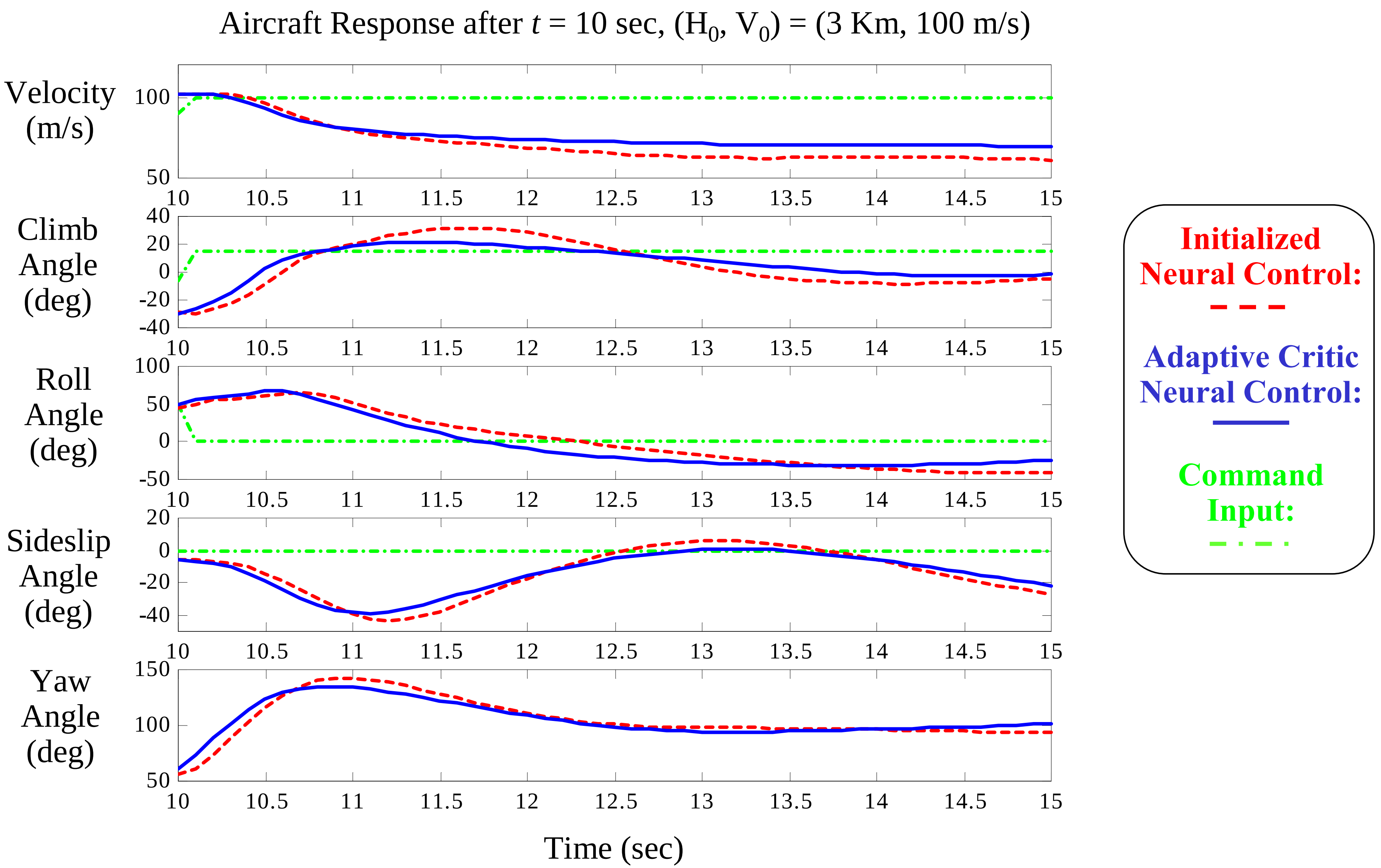
Aircraft Response, (H_0, V_0) = (3 Km, 100 m/s)



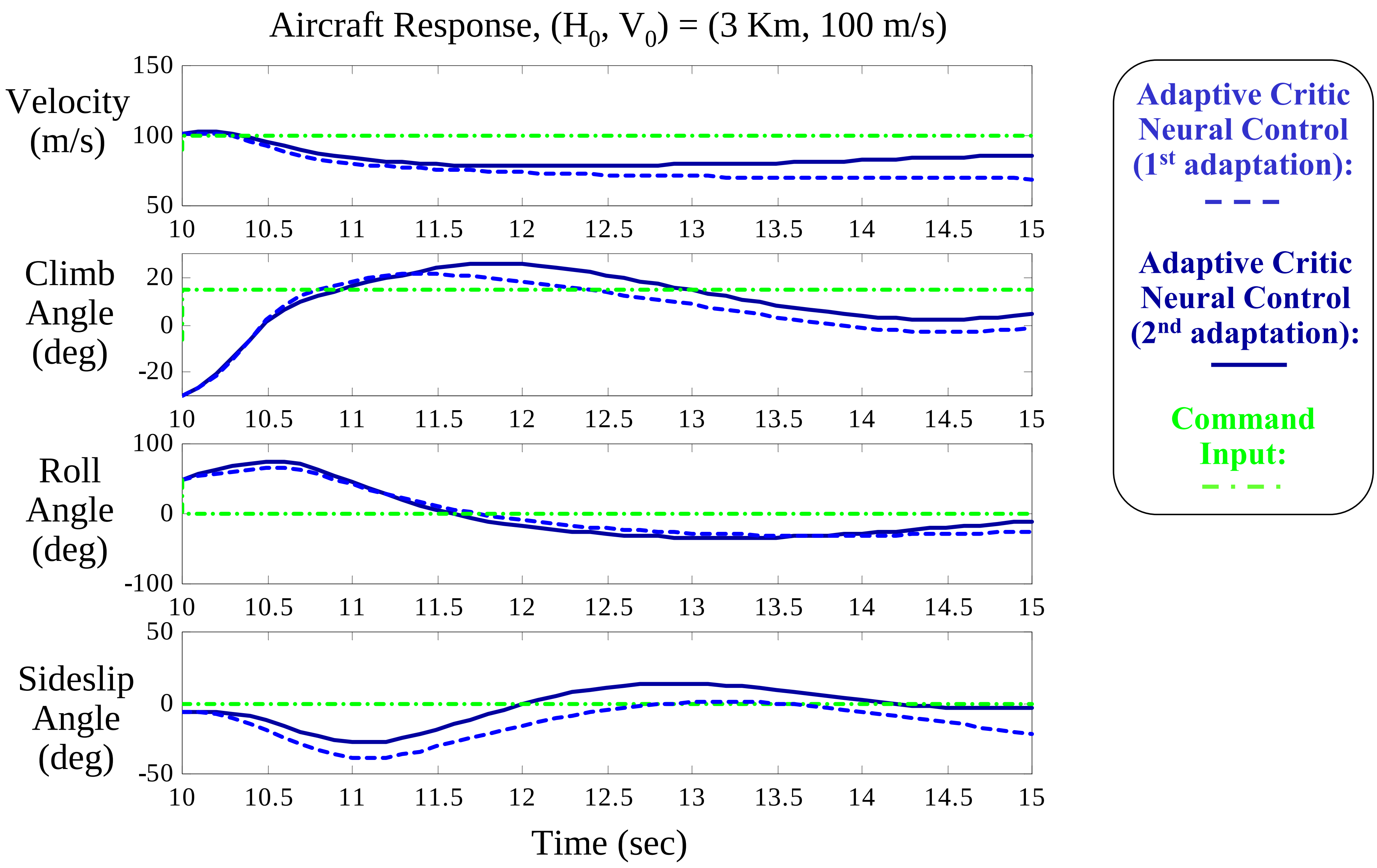
Control History



Comparison of Adaptive Critic and Initialized Neural Control: Aircraft Response in the Presence of Control Failures



Adaptive Critic Neural Control During a Previously-Encountered Maneuver



Summary of Results

Learning control system:

- Improves global performance
- Preserves prior knowledge
- Suspends and resumes adaptation, as appropriate

Achievements:

- Systematic approach for designing adaptive control systems
- Framework for investigating neural approximation properties
- Innovative (off-line and on-line) training techniques

Other Potential Applications for Adaptive Neural Control:

Air-traffic management, reconfiguring hardware (raw chips), process control, criminal profiling, image processing, ...

Flight Control Systems That Learn

Silvia Ferrari
Advisor: Prof. Robert F. Stengel
Princeton University

FAA/NASA Joint University Program on Air Transportation,
NASA Ames Research Center, Moffett Field, CA

April 4-5, 2002